DATACLYSMIC

101 COLLECTION

NUMERICAL HIERARCHICAL CLUSTER & MALL CASE

R CODING #CLUSTER #DATA_VIS

VERSION 01

Photo by Jimmy Chang

THE EXPERIMENT

TITLE:	Numerical hierarchical cluster & Mall case
VERSION:	01
DESCRIPTION:	Use of clusters for better understating a mall base customer.
DATA SOURCE:	https://www.kaggle.com/datasets/akram24/mall-customers
CODE:	GitHub

101 COLLECTION – About

This Dataclysmic collection explores a series of experiments where different chapters of BI are developed with applied cases.
This is the final report, the reader also can have access to the web post and the code that support this document, see the links above.

The 101 COLLECTION seeks to inspire the reader to find meaning in the tools that data and code allows, to think beyond the screen and wonder about the value proposition, to be creative and reflect over real application of this capabilities.

EXECUTIVE SUMMARY

This experiment uses the Hierarchical Cluster in order to understand the characteristic of the principal groups of customers of a given mall (the Mall) in order to find insights and propose actions.

EXPERIMENT NOTES

The process

We run a process of average hierarchical cluster using the Euclidean method for a data base that describe different characteristics for the customer of the Mall. Age, Annual income, gender, and Spending Score, (Spending.Score..1.100.).

The result

5 clusters of customers were identified as you can see on the right.

Initial notes

The power of each cluster (Power Cluster) was determined by the size of the cluster (the proportion among the sample) and the Spending Score. That is, that the biggest clusters with the top Spending Score have more power and are the best performance cluster for the Mall

Main Insights

- There are 3 top performance clusters the 2nd, 3rd, and 4th. (check on Power_cluster section in the right chart)
- The 4th one has the best overall Spending score 82.1, but the 2nd, and 3rd, are bigger clusters, that is how the power of this clusters makes these top performers.
- The 5th cluster has an important size 17%, and an attractive profile with a good income but does not have a good Spending Score.
- Gender did not show significance change on the behavior of profile.

KEY TAKE AWAYS

Identify different clusters allows to recollect different insights for each profile, even more allows to propose craft strategies for each cluster according to the particular context and the company objectives.

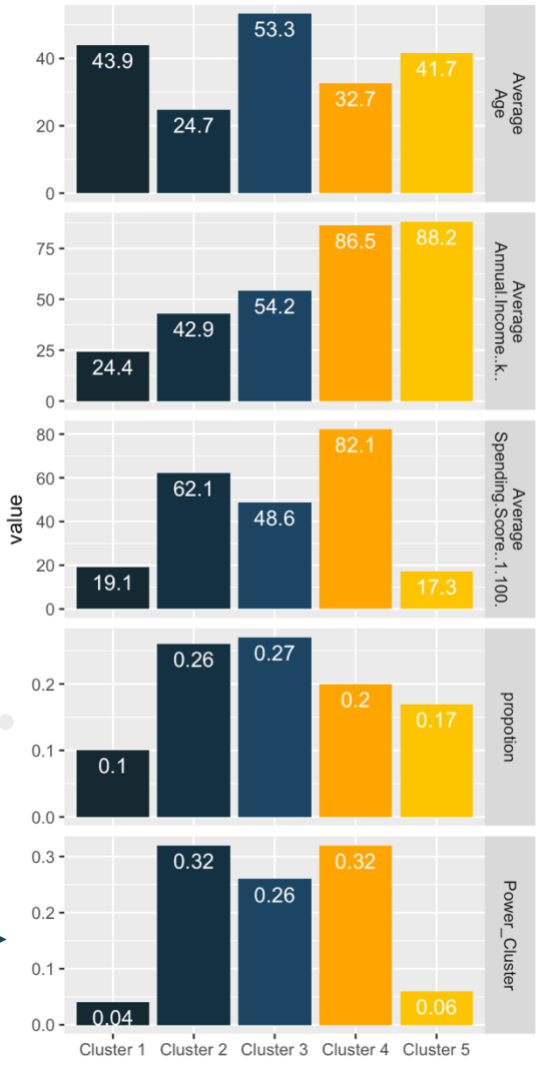
Some of those:

- The 4th cluster has a good spending score but is not the biggest in the mall, this can be a challenge for external communication. Once these clients are in the Mall, they tend to spend, but need to be attracted to the site.
- The 5th cluster shows an attractive profile, and has an important share of the customers, but they don't spend as much. The challenge here can be about the

CLUSTER CHARACTERISTICS

Variables	Type
Gender	character
Age	integer
Annual.Income..k..	integer
Spending.Score..1.100.	integer

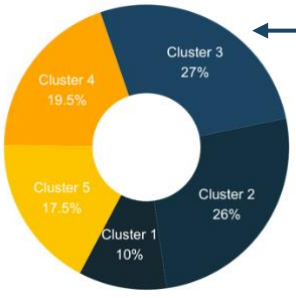
CLUSTERS SUMMARY



POWER CLUSTER ANALYSIS

This considers the average wight of the spending score in relation of the size (Proportion) of each cluster.

CLUSTER PROPORTION



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1. INTRODUCTION

This document pretends to show the process of a Cluster experiment in an applied case. The link for the R code can be find in the first page.

As always, the interest in Dataclysmic is to conjugate different elements to show value in the of analytics in a feasible context.

THE CASE

We want to target the mall efforts in marketing, product development and in general how the mall can focus on resources of the actual merchants or future ones. The clusters can give insights for a former optimization.

2. FIRS LOOK

Always know your data first. The data set is composed by 4 variables as follows:

	class_summary
Gender	character
Age	integer
Annual.Income..k..	integer
Spending.Score..1.100.	integer

The Spending Score would be our main variable of interest for the case given the context and purpose.

3. FIRST CHECK OF OUTLIERS

Age	Annual.Income..k..	Spending.Score..1.100.
Mode :logical	Mode :logical	Mode :logical
FALSE:200	FALSE:200	FALSE:200

All the results turn in to false in this first verification of outliers

4. SCALE THE DATA

The data is scaled to avoid large numbers to dominate the model, you can see the difference in range between the two summary tables

ORIGINAL DATA

Age	Annual.Income..k..	Spending.Score..1.100.
Min. :18.00	Min. : 15.00	Min. : 1.00
1st Qu.:28.75	1st Qu.: 41.50	1st Qu.:34.75
Median :36.00	Median : 61.50	Median :50.00
Mean :38.85	Mean : 60.56	Mean :50.20
3rd Qu.:49.00	3rd Qu.: 78.00	3rd Qu.:73.00
Max. :70.00	Max. :137.00	Max. :99.00

SCALED DATA

Age	Annual.Income..k..	Spending.Score..1.100.
Min. :-1.4926	Min. :-1.73465	Min. :-1.905240
1st Qu.:-0.7230	1st Qu.:-0.72569	1st Qu.:-0.598292
Median :-0.2040	Median : 0.03579	Median :-0.007745
Mean : 0.0000	Mean : 0.00000	Mean : 0.000000
3rd Qu.: 0.7266	3rd Qu.: 0.66401	3rd Qu.: 0.882916
Max. : 2.2299	Max. : 2.91037	Max. : 1.889750

5. BUILD THE CLUSTERS

Th method uses is the average Euclidean

The best partition in is determinate by 5 clusters

6. THE CLUSTERS PROFILE

COMPOSITION OF EACH CLUSTER

Each cluster is composed by 4 variables:

Variables	Type
Gender	character
Age	integer
Annual.Income..k..	integer
Spending.Score..1.100.	integer

SUMMARY OF THE CLUSTERS

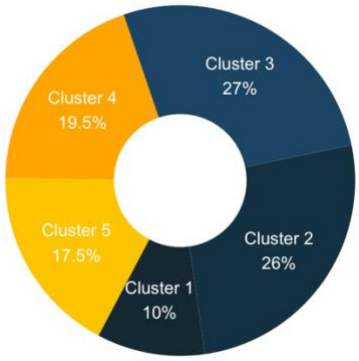
The first statistics and parameters are summarized bellow

Cluster	Count	propotion	Average Age	Average Annual.Income..k..	Average Spending.Score..1.100.	Female	Male
Cluster 1	20	0.100	43.9	24.4	19.1	60.0%	40.0%
Cluster 2	52	0.260	24.7	42.9	62.1	61.5%	38.5%
Cluster 3	54	0.270	53.3	54.2	48.6	59.3%	40.7%
Cluster 4	39	0.195	32.7	86.5	82.1	53.8%	46.2%
Cluster 5	35	0.175	41.7	88.2	17.3	42.9%	57.1%

The proportion field reflects the size of the cluster in the sample.

7. CLUSTER ANALYSIS

The objective in the case is to identify insights about the customers, punctually the analysis would be focus on the Spending Score ("Spending.Score..1.100"), this will indicate the performance and interest of action for each cluster.



SIZE OF THE CLUSTERS

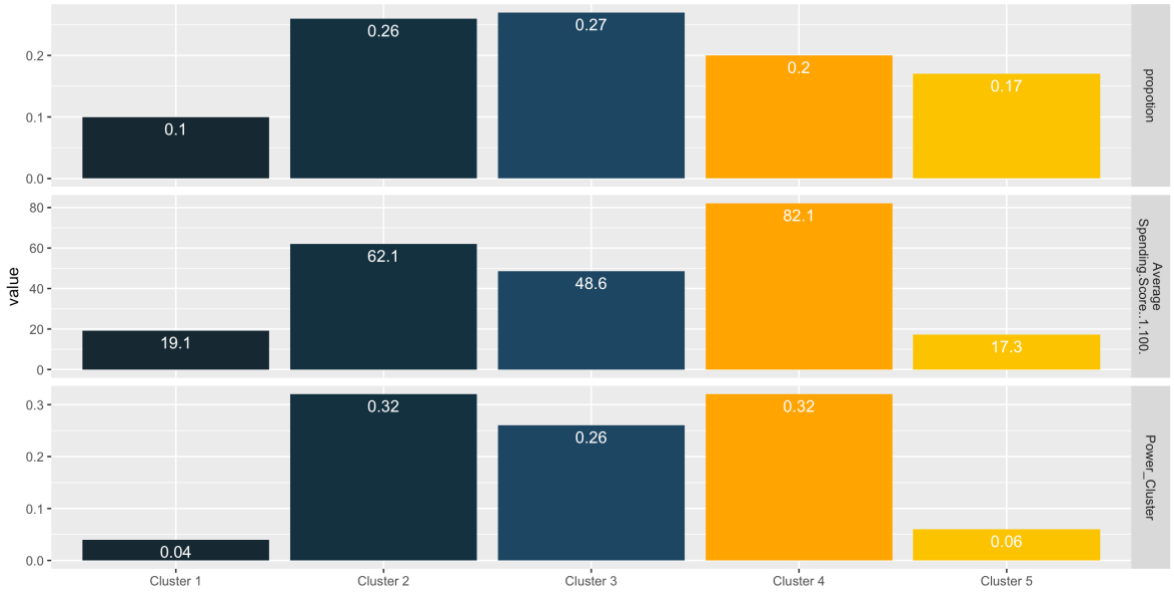
This has impact in the decisions that can be taken by the mall having in to account the size of each clusters

THE POWER CLUSTER ANALYSIS

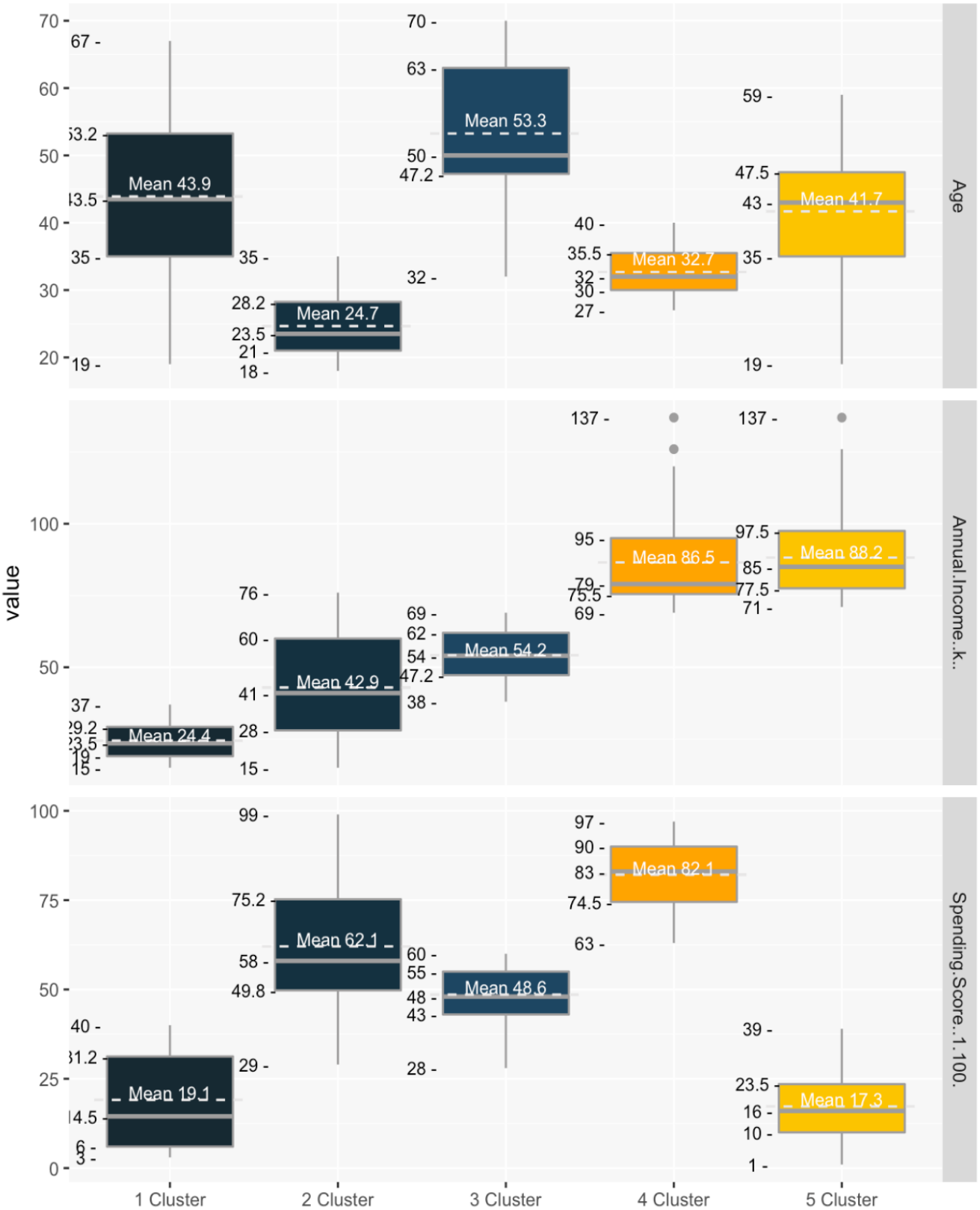
The Power cluster shows a weighted average of the Spending Score. This reflects, as the name says, the power of each cluster when you consider the size and the willing to spend.

The best performance cluster is the 4th one with an Average spending Score of 82,1. Nevertheless the consideration the proportion of the clusters 2nd and3rd adds the 53% of the compositions, that is the 32% and 26% respectively of the weighted averages of the spending score. As it is shown in the Power_Cluster section bellow.

This bring up front that the main clusters are the 2nd, 3rd, and 4th in according to the spending impact for the Mall, and not just the 4th one.



8. THE CLUSTERS PROFILE



TAKE AWAYS ABOUT THE EXPERIMENT

This are some of the conclusions that can be said, among many others and in a different and dipper analysis that goes beyond this document.

The main point is that clusters allow companies and department to identify profiles - not just for customers, think about speech (NLP) or human work force (think about application in RRHH), - and from there develop different strategies for each segment that is according to the particular context and the objects of the organizations.
Below you can find some illustrative examples.

OPPORTUNITIES: ABOUT THE WORST PERFORMERS

The worst performer clusters (the lowest Spending Score) are 1 and 5.

Cluster 1:
The performance might be because of the intuitive reason of a low income and the consequences that this has. In the case that this is a strategic segment according to the Mall business model it would be worth to analyze the services and products that the mall is offering to fulfill accessible goods for adults between 35 and 53. Probably, because of the range of age, families looking for less expensive experiences.

However, this cluster is the 10% of the base customers of the Mall, perhaps not making it a significance participation in the customers share and engaging this market could risk a conservative return against the efforts of the administration. Finance calculations should join these efforts.

Cluster 5:
Different from the 1st cluster, this segment has a better income, and represent the 17% of the participation of the Mall costumer's base. The Mall already has the customers, but they are not expending as much as the top performers as a high Spending Score. They have the market, the "right" profile, just they are not buying as the other clusters.

If the Mall could evaluate strategies to offer more experiences and products for this Cluster. Should analyze if the brans and merchants fulfill the necessities for adults between 35 and 47 with a good income: They are missing luxury brands? Do the services that they look are not in the Mall? Or figure out if something in the customer experience is going wrong. How is the Mall VOC program?

OPPORTUNITIES: ABOUT THE BEST PERFORMERS

The previous does not mean to neglect the other clusters, even more, the top performers (best size and spend score) can be motivated to attract other segments or customers with propositions, discounts, cross selling, and so on, that involves interaction among clusters. Marketing can explore some strategies.

This clusters can develop into **ambassadors** and help to grow not just they own cluster but the other segments as well if the correct strategies are executed.

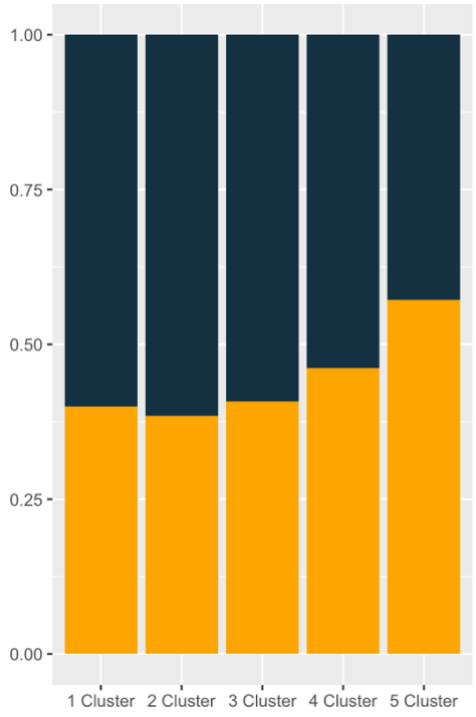
About Cluster the 4th: it sems a good profile of consumer, but share is not the highest, more costumers with this profile can be attracted to the company. Once this segment is in the Mall, they spend. That said it can be more an external communication problem. Marketing could check the interaction with this type of customers.

9. COMPLEMENTARY ANALYSIS

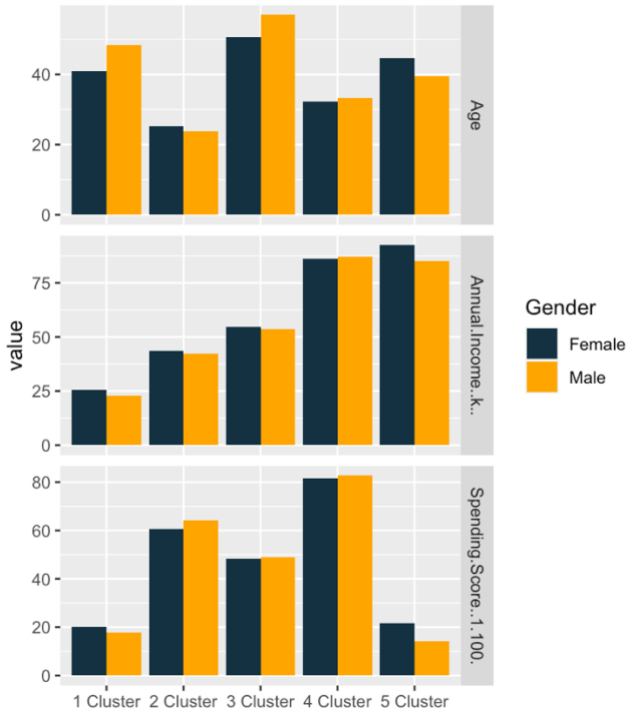
More insights and conclusion can be extracted from the dataset and the case context, in this section some of those are presented.

CATEGORICAL ANALYSIS: GENDER BEHAVIOR

CLUSTER GENDER COMPOSITION



BEHAVIOR OF GENDERS AMONG CATEGORIES

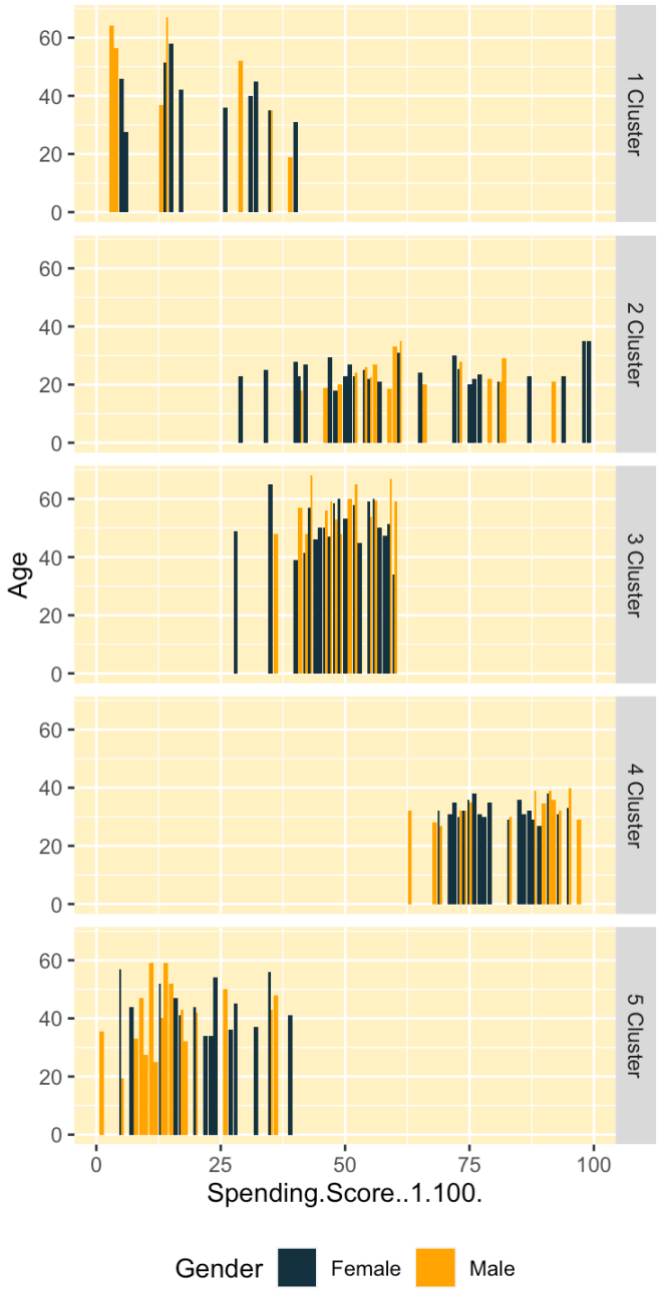


There is not much variable behavior or distribution among the genders when compared with the other variables.

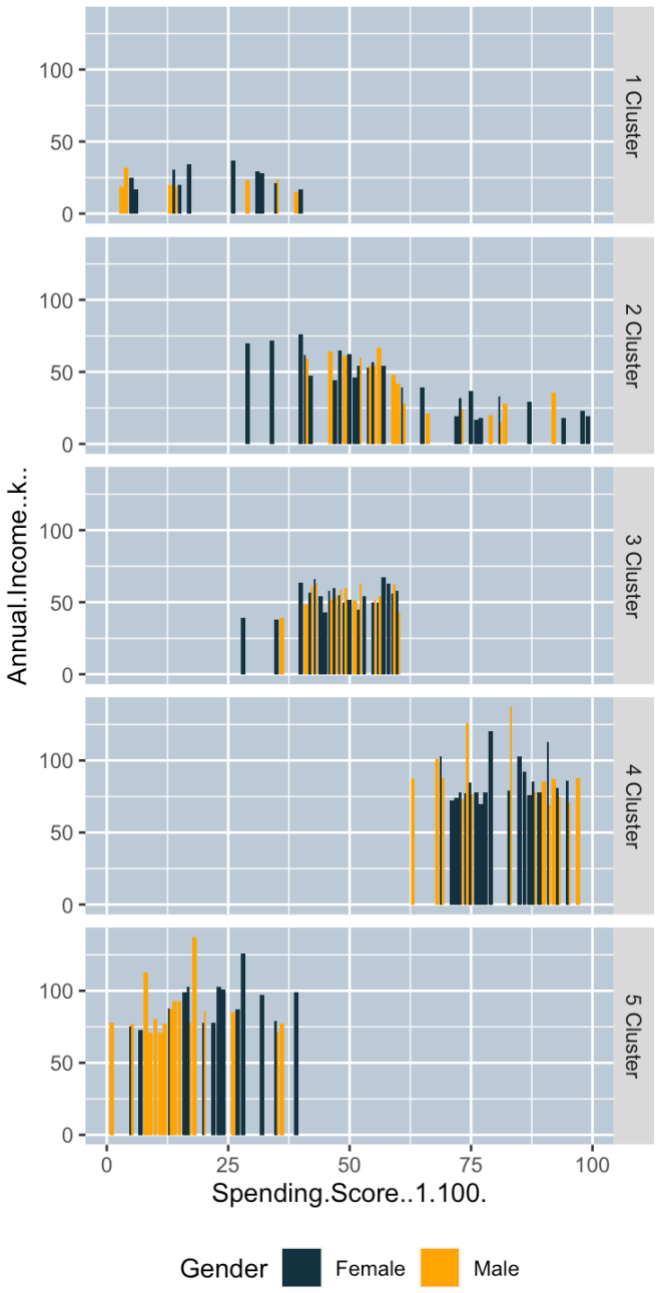
VARIABLES AGAINST THE SPENDING SCORE

This allows to identify patrons in a 2D comparation helped by the cluster classification. At first sight the disperse is the 2nd Cluster.

AGE Vs. SPENDING SCORE



INCOME Vs. SPENDING SCORE



10. FINAL NOTES AND DESCALIMAR

Some more considerations should be considered for a formal development. Pay attention to the rigor of the math, statistics, and data cleaning in further incursions. E.g., the boxplot showed some probable outliers that should be investigated.

ALWAYS LOOK FOR VALUE

Finally, it must be reenforce that the purpose of this technologies is to create value. That is the challenge in this collection, inspire to look real value, make the reader question about the purpose of all this mare magnum of data and technologies, and the why behind it.

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